A stock-flow cohort model of the national car fleet

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Abstract

Stock-flow cohort modelling of the car fleet is a powerful and handy tool for policy analysis. Even quite simple and straightforward accounting relations may provide important insights into the dynamics of fleet development. A particularly useful piece of information concerns the amount of inertia involved, as characterised, e. g., by the time lag between technological improvements affecting new vehicles and their penetration into the car fleet.

The BIG stock-flow cohort model of the Norwegian passenger car fleet constitutes a bottom-up approach to vehicle fleet forecasting. New car registrations follow from a disaggregate discrete choice model based on two decades of complete sales data for individual passenger car models. The flows and stocks characterising the car fleet are specified at a somewhat coarser, yet relatively detailed level, describing each year's stocks and flows of vehicles as the aggregation of 22 x 31 = 682 mutually exclusive and exhaustive cells. This accurate bottom level accounting guards against gross errors of aggregation, without, of course, preventing the model user from producing and presenting results at a much less detailed level. Relying almost exclusively on administrative records available from government or corporate agencies, our approach does not depend on costly household data collection or on any other type of stated or revealed preference survey.

It is possible to incorporate, into the stock-flow modelling framework, interesting and useful behavioural relations, explaining aggregate passenger car ownership and travel demand, scrapping and survival rates, or consumer choice in the market for new cars. Even without such behavioural relations, the framework is useful for analysing and predicting policy dependent developments in terms of energy use, greenhouse gas emissions, local pollution, accident rates, fiscal impact and economic costs.

Far from presupposing sophisticated computer programming, the recursive stock-flow cohort model can be implemented by means of standard spreadsheet software.

Key words:

Passenger cars, fleet forecasting, fuel economy, greenhouse gas, recursive model, bottom-up

1 Introduction and rationale

The prospect of having two billions private cars roaming the planet's streets and roads, while spewing out greenhouse gases as well as local pollutants, is discomforting (Sperling and Gordon 2009). Responsible governments worldwide are contemplating how to prevent the motor vehicle stock from reaching unsustainable levels and/or to decouple income and travel demand growth from environmental degradation and climate change (OECD 2002). In most OECD countries, passenger cars constitute the primary source of greenhouse gas (GHG) emissions from transport.

The European Commission has mandated maximum CO_2 emission targets for new passenger cars sold in 2015 and 2021, respectively. The targets are 130 grams of CO_2 per km in 2015 and 95 g/km in 2021, as measured by the NEDC laboratory test cycle. To meet the targets, automobile manufacturers are working to reduce the fuel consumption of conventional vehicles equipped with internal combustion engines (ICE), while also introducing a widening range of zero and low emission vehicles, such as battery electric (BEV) and plug-in hybrid electric vehicles (PHEV).

Similarly, the Euro 1-6 standard for light duty vehicles and the Euro I-VI standard for heavy duty engines oblige manufacturers to fulfil steadily more demanding requirements in terms of nitrogen oxide (NO_X), particulate matter (PM), hydrocarbon (HC) and carbon monoxide (CO) emissions.

A common feature of the approaches taken in OECD countries is that the regulatory and fiscal policy instruments operate primarily – or exclusively – on the newest generation of cars. If one can make sure that the next generation of vehicles is consistently more eco-friendly than the previous one, the car fleet will be steadily improving in terms of its environmental footprint.

But how fast will this improvement take place? The need to reduce the annual amount of GHG emitted into the atmosphere is an urgent one (IPCC 2013). Hence the speed at which the adverse effects of private car use will be mitigated through the normal vehicle renewal process, or through an accelerated one, carries considerable interest. How long will it take for a new technology to penetrate (almost) the entire car fleet? How fast can we lower the fleet's mean CO_2 emission rate? If certain technologies, such as combustion engines, were to be banned from *new cars,* how long would it take before emissions from the *car fleet* had dropped by, say, 50 percent? Is it possible to reduce CO_2 emissions from cars by 70 percent by 2050, in line with targets suggested by IPCC ? If so, what kind of policy measures would be required?

In Norway, the government has set a CO_2 target of maximally 85 g/km emitted, according to the type approval tests, from new cars sold in 2020 on average. While there is no domestic car manufacturing, the ownership and use of zero emission vehicles – BEVs and fuel cell electric vehicles (FCEV) – enjoy substantial fiscal and regulatory incentives. These vehicles are exempt of value added tax (VAT), vehicle purchase tax, road tolls and public parking charges. They benefit from strongly reduced annual circulation tax and ferry fares. Moreover, they are generally allowed to travel in the bus lane and may be parked and recharged for free in many public parking lots.

Also, the vehicle purchase tax payable upon first registration in Norway strongly penalises conventional cars with high CO_2 emission rates, be they petrol or diesel driven, while low emission vehicles, such as PHEVs, may in the best of cases come out with almost no purchase tax[1].

The stock of vehicles, be it at the global, national, local or company level, is the result of several flows operating over time: new registrations, scrapping, and second hand import and export. To keep track of how fast technological developments and other changes in the attributes of new vehicles penetrate into the vehicle fleet, a stock-flow cohort model approach is an obvious methodological choice. We have therefore set out to develop a detailed, comprehensive and coherent vehicle turnover model for the Norwegian passenger car fleet.

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[1] See companion paper by Fridstrøm and Østli (2015)

While ours is not the first stock-flow model of the passenger car fleet[2], few – if any – of these modelling efforts have been exhaustively described in the scientific literature. Our paper should help fill this gap. It aims to illustrate the fruitfulness of the stock-flow vehicle cohort approach, while also demonstrating the wealth of relevant information accessible through a rigorous and detailed bottom-up accounting system for passenger car segments and their respective attributes. Relying almost exclusively on administrative records available from government or corporate agencies, our approach does not depend on costly household data collection or on any other type of stated or revealed choice survey.

In Section 2, we describe the general structure and segmentation used in our BIG[3] model of the Norwegian passenger car fleet, while also presenting a first picture of the car stock, by segments and age, as of our base year 2012. In Section 3, we show how the systematic information put into the model can be used to derive a host of intermediate results, such as mileage patterns, CO_2 emission developments, retail price trends, market shares, vehicle survival rates and life expectancy. In Section 4, as an example of potential applications, we present a set of scenario projections illustrating the impact of a low carbon fiscal policy. Certain strengths, weaknesses and opportunities to our approach are discussed in Section 5. Conclusions are drawn in Section 6.

2 Model structure and empirical foundation

The BIG model splits the car stock into 22 segments and 31 age classes. There are nine segments for petrol driven cars and nine for diesel driven ones, each fuel class being subdivided into weight classes. In addition, there is one segment for hybrid vehicles (HEVs, including PHEVs), one for BEVs, one for FCEVs, and one for vehicles using other energy carriers (compressed natural gas, ethanol, etc).

The segmentation is based on objective criteria only. We have chosen to avoid the commonly accepted segmentation into 'compact' cars, 'mid-sized' cars, 'luxury' cars, etc., for the simple reason that these labels are to some extent subjective and hence elusive. Relying on objective measurements, we will always be able to know how to classify a given vehicle, and even a hypothetical one, as long as its engine type and curb weight are declared.

The composition of the Norwegian passenger car fleet as of 31 December 2012 is shown in Figure 1.

One notes that, while older vehicle generations are made up predominantly by petrol driven cars, diesel driven vehicles have become more frequent from the 2007 cohort onwards. In later years BEVs and HEVs have acquired noticeable market shares.

Vintage cars older than 30 years are fairly numerous in Norway. These are exempt of the purchase tax otherwise payable upon registration and subject to a strongly reduced annual circulation tax.

The recursive structure of the BIG forecasting algorithm is shown in Figure 2.

To each cell in the 22 x 31 matrix of the car fleet, various attributes are assigned, such as mean type approval fuel consumption per km, mean annual distance driven, annual rate of scrapping, and an annual rate of second hand (used car) import. There is also a residual outflow of vehicles defined, with its own annual rate, covering second hand vehicle export and net temporary or permanent deregistration[4]. We shall refer to the sum of scrapping and residual net deregistration as the total 'attrition'.

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[2] A fairly well-known model of this kind is the Dutch DYNAMO model (Meurs et al. 2006, 2013). Also, Hugosson et al. (2014) describes a car fleet model for Sweden.

[3] BIG is an acronym for 'car generation model' – 'bilgenerasjonsmodell' as spelt in Norwegian.

[4] By 'scrapping', we mean turning the car in to an authorised vehicle recycling facility, whereby the scrap deposit payable upon the vehicle's first registration is reimbursed. Residual net deregistration covers all those cases where the vehicle is removed from (Norwegian) roads, however without the owner collecting the scrap deposit. Net deregistration could be negative, if more vehicles are reregistered than deregistered. It is not uncommon for owners to temporarily hand in the vehicle's license plates, i. e. to deregister the car, so as to avoid paying the annual circulation tax.

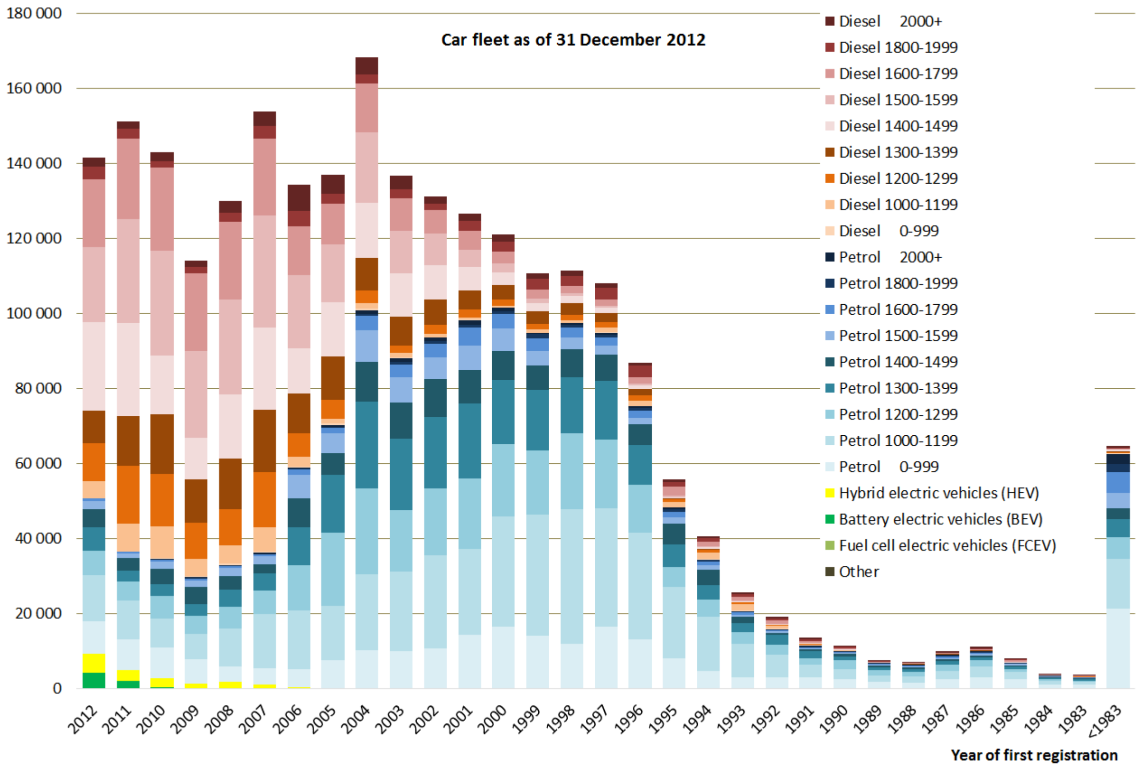

Figure 1. The Norwegian passenger car fleet at year-end 2012, by fuel type, kg curb weight and year of first registration.

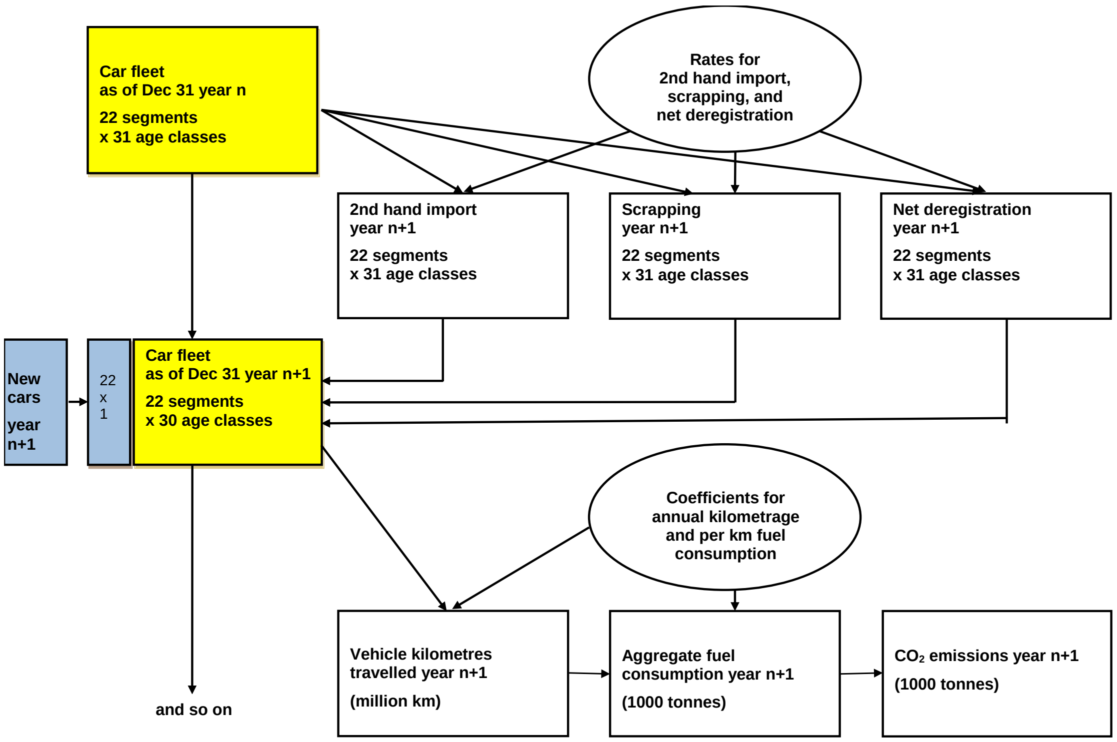

Figure 2. Flowchart of the BIG stock-flow cohort model of the Norwegian passenger car fleet.

Let $A_{i,j}^{n}, (i=1,2,....,22;\ j=1,2,...,31)$ denote the number of vehicles in segment *i* and age class *j* at the end of year *n*. Also, let $b_{i,j}^{n}$, $s_{i,j}^{n}$ and $d_{i,j}^{n}$ denote, respectively, the used car import, the scrapping, and the net deregistration of vehicles in segment *i* and age class *j* during year *n*.

For notational clarity, we use capital letter symbols for stocks, while lower case letters denote flows. For coefficients, we shall use lower case Greek letters.

Now, the following accounting identities apply:

$$\begin{aligned}(1)\quad A_{i,j+1}^{n+1} &= A_{i,j}^{n} + b_{i,j+1}^{n+1} + s_{i,j+1}^{n+1} + d_{i,j+1}^{n+1}\\ &= A_{i,j}^{n} + \beta_{i,j+1}A_{i,j}^{n} + \sigma_{i,j+1}A_{i,j}^{n} + \delta_{i,j+1}A_{i,j}^{n}\\ &= A_{i,j}^{n}\left[1+\beta_{i,j+1}+\sigma_{i,j+1}+\delta_{i,j+1}\right] \quad (j=1,2,...,30),\end{aligned}$$

where we have defined the used car import, scrapping and net deregistration *rates*

$$(2)\quad \beta_{i,j+1} = b_{i,j+1}^{n+1}\big/A_{i,j}^{n}, \quad \sigma_{i,j+1} = s_{i,j+1}^{n+1}\big/A_{i,j}^{n}, \quad \delta_{i,j+1} = d_{i,j+1}^{n+1}\big/A_{i,j}^{n}.$$

Most cars survive until the next year. The *j*'th youngest cohort in year *n* becomes the *j*+1 youngest cohort in year *n*+1. In addition, second hand vehicle import augments the stock of vehicles within segment *i* and each age class *j* by a fraction $\beta_{i,j}$ of the stock at New Year. Similarly, scrapping and deregistration mean that each year there is some attrition. Here, for notational simplicity, we have assumed that the used car import, scrapping and deregistration rates are constant, i. e. they do not depend on the year *n*. In practical model applications, this default option may or may not be adhered to.

From the Norwegian motor vehicle registry we extracted the following vehicle stock, used car import and scrapping data for 2010, 2011 and 2012:

$$A_{i,j}^{2010}, A_{i,j}^{2011}, A_{i,j}^{2012}, b_{i,j}^{2011}, b_{i,j}^{2012}, s_{i,j}^{2011}, s_{i,j}^{2012} \quad (i=1,2,...,22;\ j=1,2,...31).$$

From these data we estimated the following used car import and scrapping rates:

$$(3)\quad \hat{\beta}_{i,j} = \frac{1}{2}\left[\frac{b_{i,j}^{2011}}{A_{i,j-1}^{2010}} + \frac{b_{i,j}^{2012}}{A_{i,j-1}^{2011}}\right], \quad \hat{\sigma}_{i,j} = \frac{1}{2}\left[\frac{s_{i,j}^{2011}}{A_{i,j-1}^{2010}} + \frac{s_{i,j}^{2012}}{A_{i,j-1}^{2011}}\right], \quad (i=1,2,...,22;\ j=2,3,...,31),$$

i. e., by taking the average empirical rates as observed over the two years 2011 and 2012.

The residual net deregistration rate was determined – how else? – residually, by taking

$$(4)\quad \hat{\delta}_{i,j} = \frac{1}{2}\left[\frac{A_{i,j}^{2011} - b_{i,j}^{2011} - s_{i,j}^{2011} - A_{i,j-1}^{2010}}{A_{i,j-1}^{2010}} + \frac{A_{i,j}^{2012} - b_{i,j}^{2012} - s_{i,j}^{2012} - A_{i,j-1}^{2011}}{A_{i,j-1}^{2011}}\right] \quad (i=1,2,...,22;\ j=2,3,...,31),$$

i. e. by solving equation (1) for $\hat{\delta}_{i,j}$ and computing the average over the years 2011 and 2012.

For *j*=1, i. e. for the youngest cohort of cars, shown in Figure 2 as the blue, left-most column of the vehicle stock matrix $\boldsymbol{A}^{n}=\left[A_{i,j}^{n}\right]$, one cannot start from cohort data taken from the previous year. A different source of information is needed.

Drawing on the software and data organising facilities of the Norwegian Road Federation (www.ofv.no), complete and detailed new car sales data were extracted for the period 1992-2011. A total of 44 087 different passenger car models enter the data set, with detailed information on, inter alia, list price, make, fuel type, type approval fuel consumption, curb weight, utility load, engine power, width, length, traction, number of doors and seats, as well as the number of units sold each year.

In the context of the BIG stock-flow model, the role of the new car sales data set is twofold. Firstly, we used the data to estimate a generic nested logit model of new car purchases, described in a companion paper by Østli et al. (2015). The consumers' choice of cars being sensitive to retail prices, the logit model can be used to predict the different vehicle models' market share under varying assumptions concerning the design of the vehicle purchase tax system. By aggregating these predicted market shares into the segments shown in Figure 1, and multiplying by an exogenously given aggregate number of new cars registered, we obtain, for each forecasting year n, the 22 x 1 vector of new car purchases forming the left-most column of the stock matrix $\boldsymbol{A}^n$.

Secondly, the data set provides a wealth of information on the characteristics of each vehicle cohort, such as segment market shares, average segment prices, and type approval fuel consumption and CO_2 emission rates, for the 1992-2011 cohorts.

Denote by $f_{i,j}^{n}$ the fuel consumption of vehicles in segment i and age class j during year n, and by $m_{i,j}$ the kilometrage of segment i cars in their jth life year. Also, denote by $\varphi_{i,j}$ denote the mean real-world per kilometre fuel consumption within segment i and cohort j, by $\tilde{\varphi}_{i,j}$ the corresponding laboratory measured, type approval fuel consumption rate, and by $\eta_{*j} = \varphi_{i,j} / \tilde{\varphi}_{i,j}$ the cohort specific ratio of real-world to type approval rates of fuel use, as established by Mock et al. (2013, 2014). For lack of better information, we assume this ratio to be uniform across vehicle segments. Also, we assume that the fuel efficiency of a cohort of passenger cars does not change with the vehicles' age. Here, again, we rely on Mock et al. (2013).

The total fuel consumption of the car fleet in year n is then calculable as

$$(5) \quad f^{n} = \sum_{i=1}^{22}\sum_{j=1}^{31} f_{i,j}^{n} = \sum_{i=1}^{22}\sum_{j=1}^{31} \eta_{*j}\tilde{\varphi}_{i,j} m_{i,j}\left[a_{i,j-1}^{n-1} + a_{i,j}^{n}\right]/2,$$

where we have weighted the fuel consumption of each cohort by the average size of the car stock[5] through year n.

Letting ε_i denote the kilogram amount of CO_2 emitted per litre of fuel consumed by cars in segment i, we compute the total amount of CO_2 emissions from the car fleet in year n by the formula

$$(6) \quad e^{n} = \sum_{i=1}^{22}\varepsilon_i \sum_{j=1}^{31} f_{i,j}^{n} = \sum_{i=1}^{22}\varepsilon_i \sum_{j=1}^{31} \eta_{*j}\tilde{\varphi}_{i,j} m_{i,j}\left[a_{i,j-1}^{n-1} + a_{i,j}^{n}\right]/2 .$$

In the BIG algorithm, we have set $\varepsilon_i = 2.316$ for hybrid (i = 1) and petrol driven cars (i = 5, 6,...,13) and $\varepsilon_i = 2.663$ for diesel driven ones (i = 14, 15,…, 22).

To obtain data on the annual mileage of cars in their jth life year ($m_{i,j}$), we have extracted odometer readings from the registry of periodic vehicle inspection. Under EU regulations, passenger cars are generally inspected at two-year intervals, the first inspection taking place about four years after the vehicle's first registration. Certain interpolations and adjustments were made in order to convert these four-year and two-year readings into consistent annual mileage estimates.

[5] By convention, we set $a_{i,0}^{n} \equiv 0 \; \forall \; i, n.$. Since, on the average, last year's cohort of cars enter the stock around mid-year, they travel only half a normal annual mileage.

For hybrid and battery electric vehicles, the empirical basis for the assessment of survival rates and mileage is scant, to say the least. As of 2012, few of these vehicles were old enough to have made their first odometer reading at periodic vehicle inspection, and too few were old enough to provide reliable statistical information on annual survival rates up to the end of the vehicles' lifespan. Moreover, since early BEV and HEV models are uncharacteristic – typically smaller and simpler – compared to later generations, it would be quite misleading to base long-term projections on the scrapping rates and mileage observed for these early varieties. Instead, provisional *ad hoc* survival rates and mileage parameters for BEVs, HEVs and FCEVs have been set similar to those of mid-size petrol driven cars, or somewhat lower. Information released by Nissan on their battery electric model LEAF[6] suggests an average annual mileage of 16 500 km, comparable to that of new ICE cars. Figenbaum et al. (2014) confirm that modern BEVs in Norway are driven 14-15 000 km per year – just about as much as the average, new petrol driven car.

Using the above framework, programmed as a set of Excel spreadsheets, we are able to simulate several paths of development, differing primarily in terms of new car entries, until the 2050 horizon.

3 Intermediate results

Interesting pieces of information can be distilled from the stock-flow modelling framework even before making the first model projection.

3.1 Survival rates and vehicle life expectancy

The sum of the scrapping and net deregistration rates translate into age and segment specific survival rates given by

(7) $$\rho_{i,j} = 1 - \sigma_{i,j} - \delta_{i,j}$$

and cumulative survival probabilities

(8) $$\pi_{i,k} = \prod_{j=1}^{k} \rho_{i,j} = \prod_{j=1}^{k} \left[1 - \sigma_{i,j} - \delta_{i,j}\right] \quad (i = 1, 2, ..., 22;\ k = 1, 2, ..., 31).$$

The life expectancy of a car within a given segment is calculable as

(9) $$\Psi_i = \pi_{i,1} + \sum_{k=2}^{30} k\left[\pi_{i,k} - \pi_{i,k-1}\right] + k^*\left[\pi_{i,31} - \pi_{i,30}\right] \quad (i = 1, 2, ..., 22),$$

where k^* is the average age of vintage cars older than 30 years. We have set this constant to 35 years.

The survival probabilities and life expectancies are exhibited in Figures 3 and 4, in which the colour codes are roughly the same as in Figure 1.

Note that in the BIG stock-flow model, life expectancy measurements exceed the vehicles' real life span, as reckoned in calendar months, by a little more than one year. This is so because, in the stock-flow model, age is counted from January 1 in the year of first registration to December 31 in the scrapping year. But on the average new vehicle enters the stock at mid-year, while scrapping is concentrated between 1 January and 20 March, since the annual circulation tax is due at the latter date.

[6] See, e. g., http://www.greencarcongress.com/2015/01/20150119-leaf.html or http://www.newsroom.nissan-europe.com/uk/en-gb/Media/Media.aspx?mediaid=128587

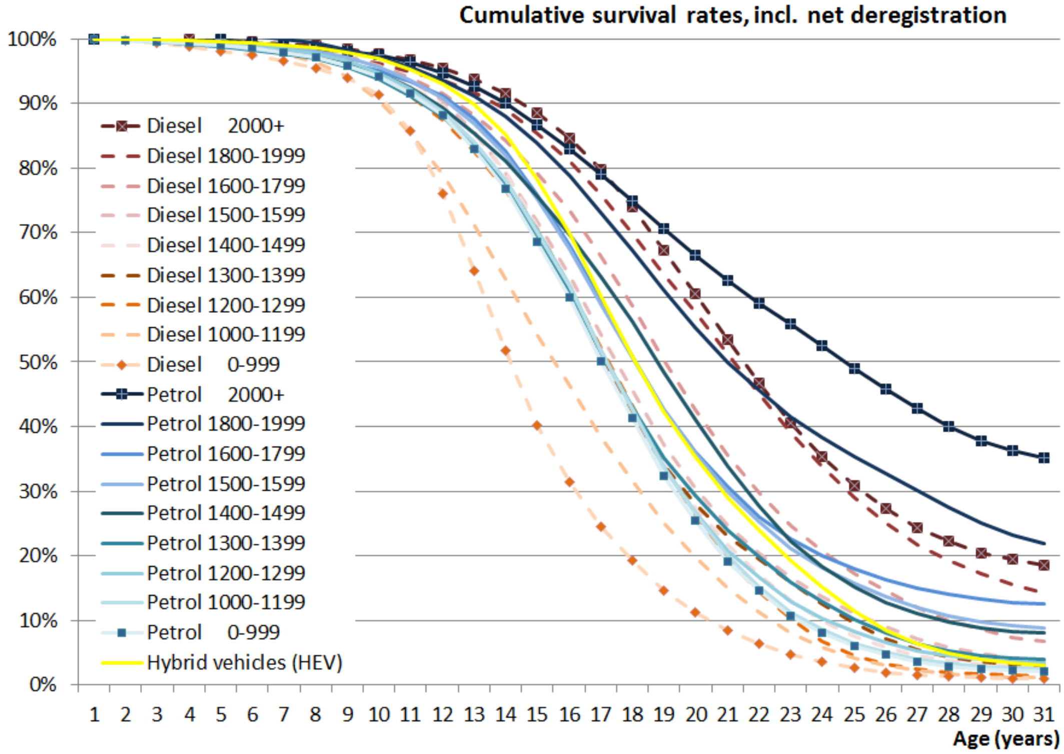

Figure 3. Cumulative survival rates of Norwegian registered passenger cars, by fuel type and kg curb weight, estimated from 2010-2012 scrapping and net deregistration flows.

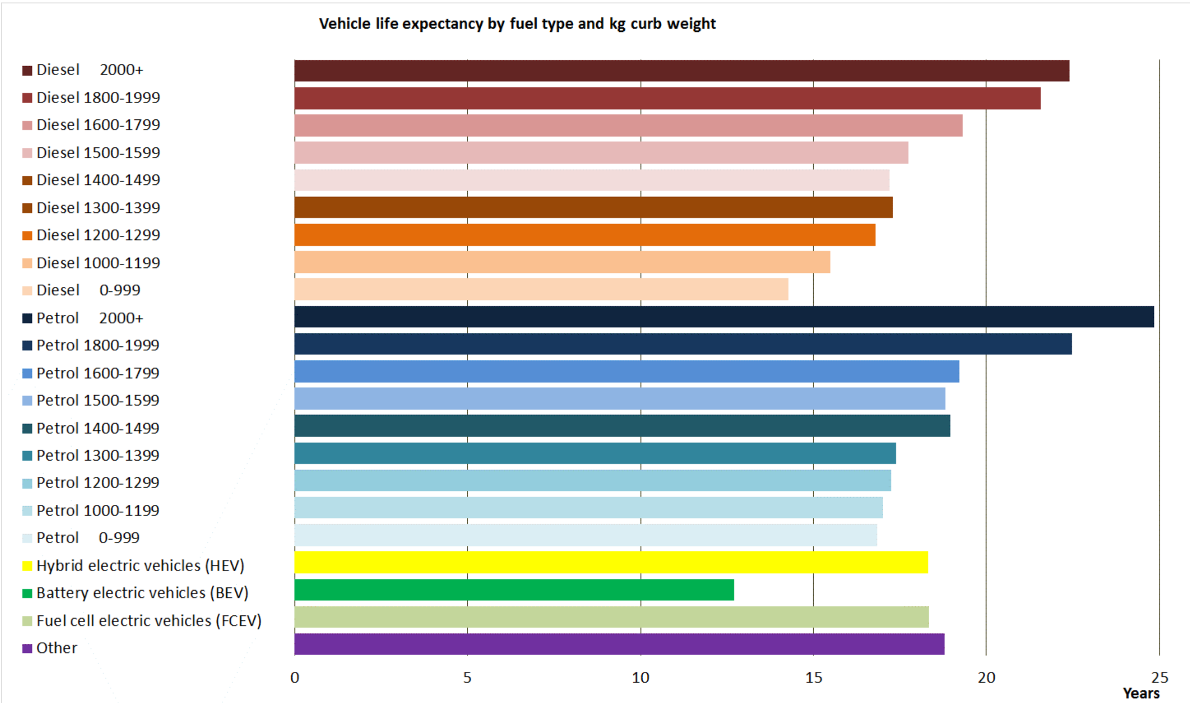

Figure 4. Life expectancy of Norwegian registered passenger cars, by fuel type and kg curb weight, estimated from 2010-2012 scrapping and net deregistration.

Larger cars live longer than smaller cars. While nearly half of the largest petrol cars last as long as 25 years, the smallest diesel cars have a median life span in Norway of only 14-16 years. The overall life expectancy of Norwegian registered passenger cars is 17.8 years, as reckoned in BIG, or roughly 16.5 years as counted from the date of first registration to the date of scrapping, export or final deregistration.

3.2 Annual vehicle kilometres travelled

The annual vehicle kilometres travelled, as distilled from the odometer readings taken during periodic vehicle inspection, are shown in Figure 5.

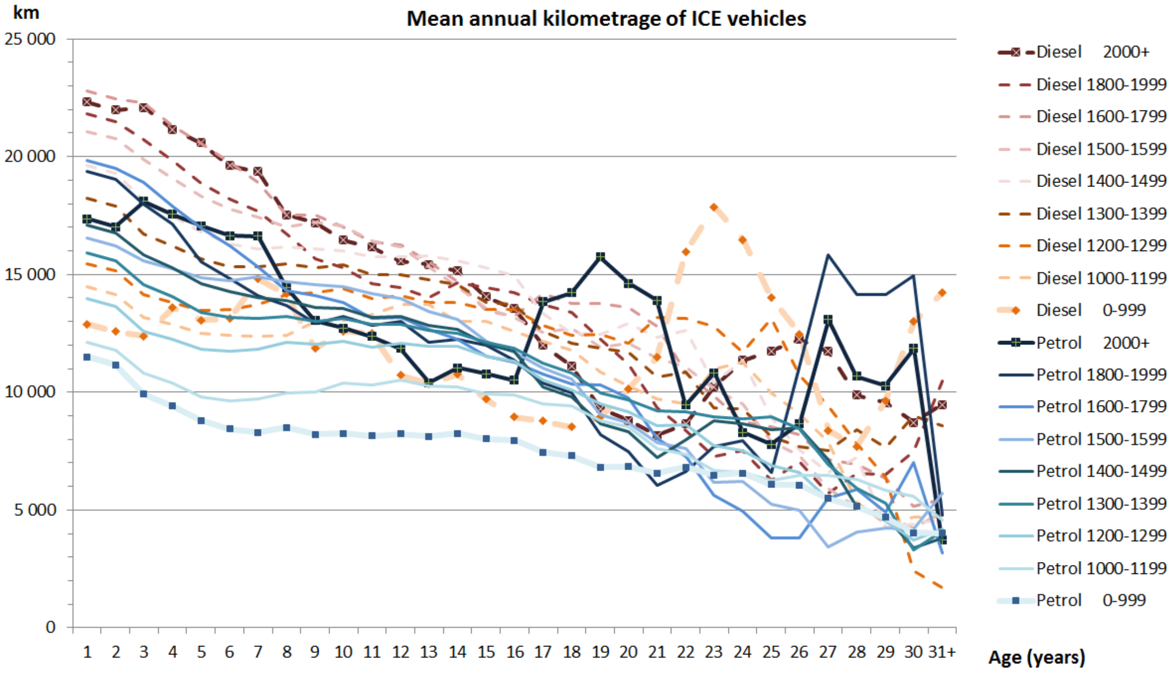

Figure 5. Average annual distance driven by Norwegian registered ICE passenger cars 2010-2012, by fuel type, kilogram curb weight and age.

Diesel driven cars travel considerably farther than petrol cars, and younger vehicles are used a lot more than older ones.

Behind the latter phenomenon there are probably two mechanism at work. Newer cars are perceived as safer, more comfortable, more fuel efficient, and generally more attractive as a travel mode, than older cars. Put otherwise, the same person would have a higher probability of choosing her own car over travelling by bus or coach, if this car is new and technologically up-to-date, than if it is old and tattered. Also, the overall trip frequency may be positively influenced by having access to a nice new car.

Secondly, since purchase decisions are made, not by the vehicles themselves, but by people, there is a selection process going on, whereby car owners with a large road travel demand tend to invest in newer and more expensive cars.

Some vehicle segments, such as the smallest diesel cars and the biggest petrol cars, exhibit seemingly erratic mileage patterns at high age. This is simply because the number of vehicles in these categories is quite small, which gives rise to pronounced random variation. We have chosen not to smooth out the empirical curves and replace them by artificial rates, since, on account precisely of the small number of vehicles affected, the potential aggregate forecasting error is quite limited.

3.3 CO_2 emission rates

The mean type approval rates of per kilometre CO_2 emissions characterising different cohorts of vehicles within each segment are shown in Figure 6. The trend is clearly downwards in all segments. Note, however, that the growing discrepancy between type approval and real-world emission rates serves to neutralise a large part of the improvement[7].

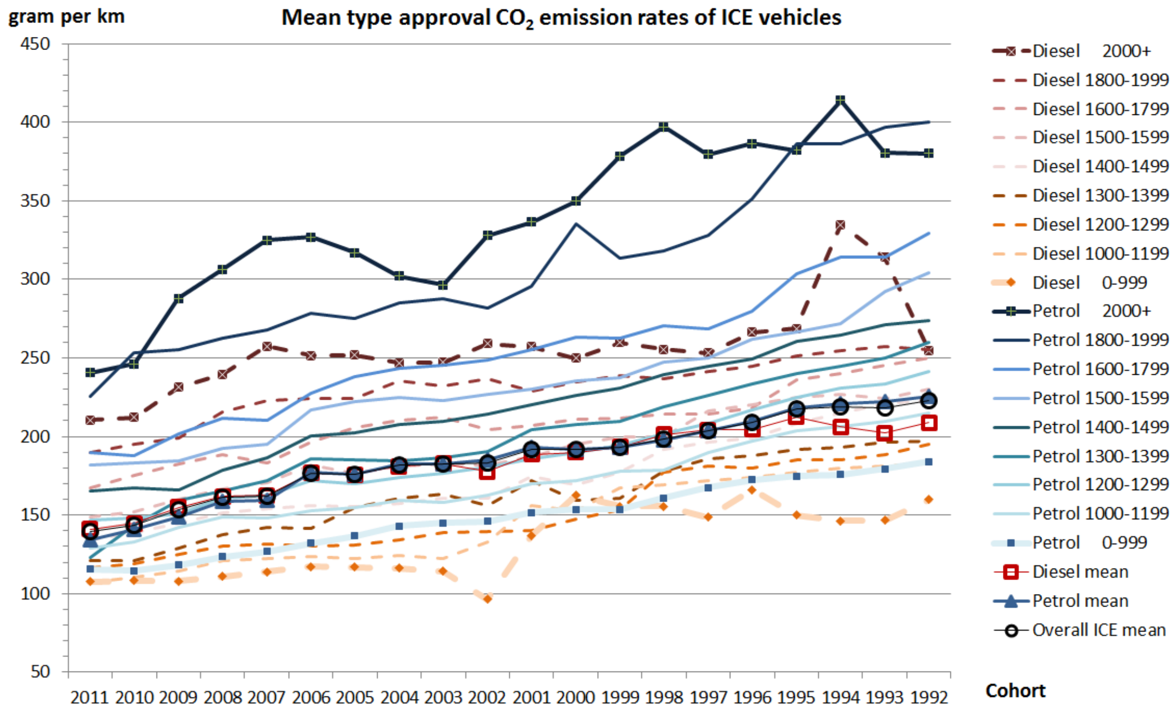

Figure 6. Average type approval CO_2 emission rates of new petrol and diesel driven passenger cars registered in Norway 1992-2011, by fuel type, kg curb weight and year of first registration.

3.4 Retail prices and market shares

In Figure 7, we show inflation corrected retail prices including tax, as reckoned in Norwegian kroner (NOK 2010)[8].

In most segments, and indeed for all segments lighter than 1800 kg curb weight, the real price is tending clearly downwards between 1992 and 2011. The mean diesel vehicle price has fallen by 13 per cent, and that of petrol driven cars by 22 per cent. And yet the average real price of all ICE cars is 0.7 per cent higher in 2011 than in 1992.

This is a case of Simpson's paradox (Simpson 1951, Blyth 1972). Since market shares have gone up for the more expensive segments, large cars gaining ground at the expense of smaller ones, and diesel cars conquering market shares from petrol cars, the weighted average has gone up, although in almost every subgroup the trend is negative.

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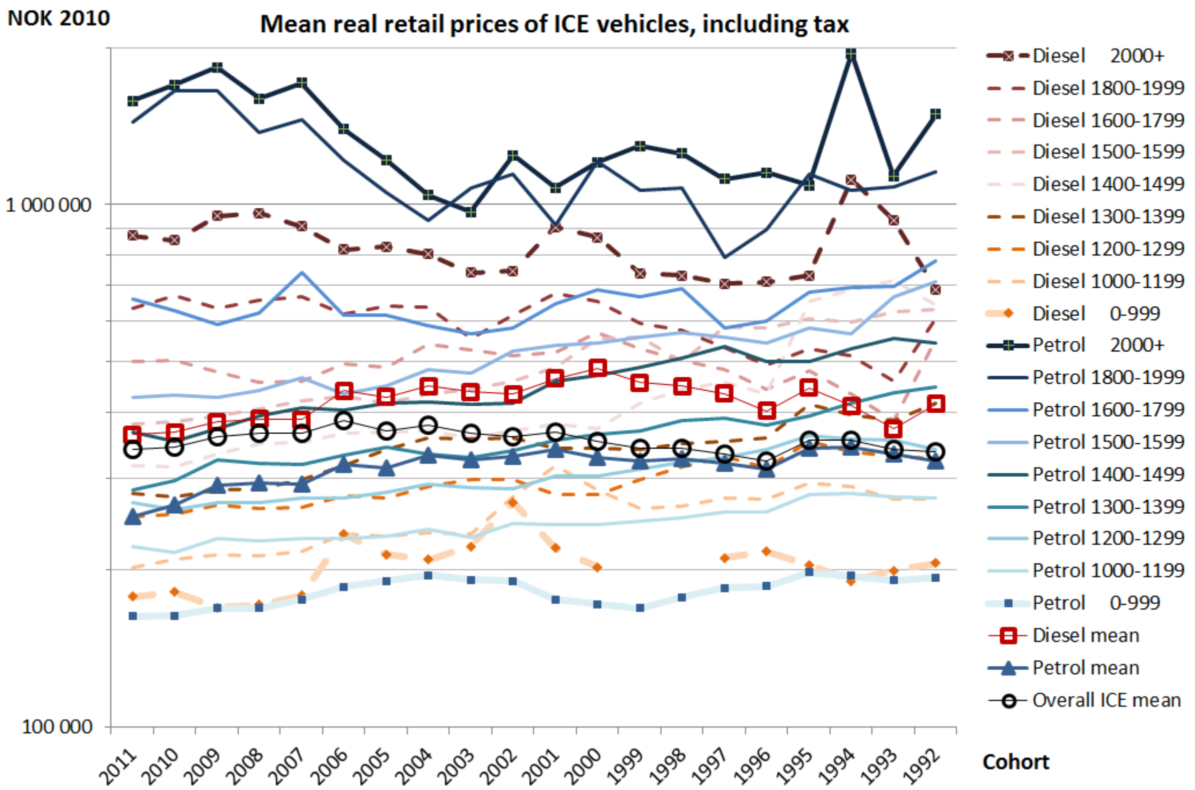
[7] As shown by Fridstrøm and Østli (2015), drawing on Mock et al. (2013, 2014), as much as 80 per cent of the 'improvement' recorded in the EU between 2006 and 2013 is fictitious.

[8] As of mid-year 2010, € 1 = NOK 8.



Figur 7. Average real retail prices of new ICE passenger cars 1992-2011, by fuel type, kg curb weight and cohort. Logarithmic scale.

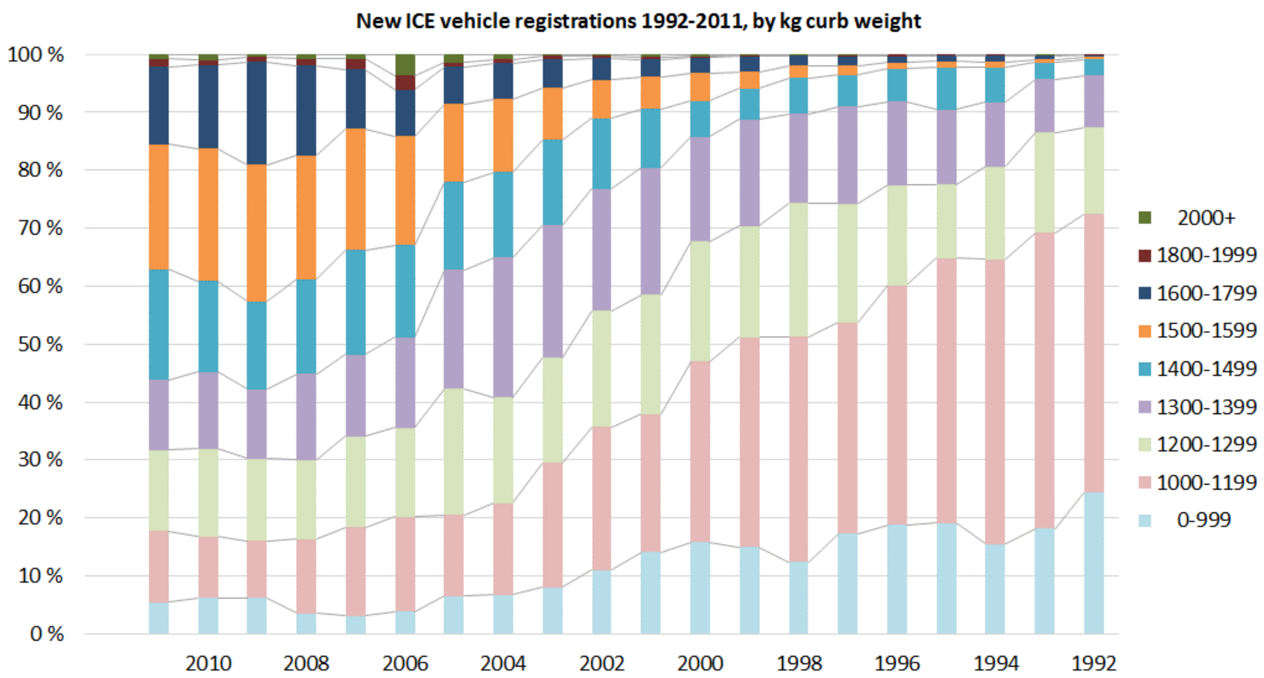


Figure 8. Weight distribution of new ICE cars bought 1992-2011, according to vehicle registration data.

While vehicles lighter than 1200 kg had more than 70 per cent of the market in 1992, their share in 2011 was under 20 per cent. Conversely, vehicles above 1400 kg curb weight have had their market share grow from less than 5 per cent in 1992 to more than 55 per cent in 2011 (Figure 8).

In Norway, purchase tax and value added tax (VAT) constitute a large share of the retail price of passenger cars[9]. The downward trends in retail prices are to some extent explicable by reduced purchase tax rates. According to the Norwegian foreign trade statistics, the mean pre-tax import values of petrol and diesel driven cars have risen by 48 and 43 per cent, respectively, in real terms between 1992 and 2011 (Fridstrøm and Østli 2015). The lowered tax rates serve to dampen the effect of this price surge, which also reflects increasing average vehicle size.

4 Scenario projections

The main objective of the BIG stock-flow model is to provide a tool for long-term policy analysis. A few applications are presented below.

In Figure 9, we show the stock of vehicles at year-end 2030 according to a reference path developed by Fridstrøm et al. (2014, 2015). In this scenario, no changes are made to the design of the vehicle purchase tax as applicable in 2014, but the tax and toll exemptions for BEVs are gradually abolished between 2018 and 2022.

One notes that even under this 'business-as-usual' scenario, hybrid and battery electric vehicles are projected to become considerably more numerous.

The 2- to 10-year old cohorts are seen to be more numerous than the youngest one. This has nothing to do with changes in the total number of new cars registered, which is assumed constant throughout our projection period. The explanation is second hand car import, which typically adds 20-25 per cent more vehicle registrations on top of the new car sales. The great majority of second hand cars imported are between two and five years of age.

In Figure 10, we show a corresponding picture from the alternative 'low carbon' policy scenario, in which the purchase tax incentives to buy low and zero emission vehicles are strengthened considerably. Here, hybrid and battery electric vehicles are seen to make up more than 50 per cent of the youngest cohort, but still only 21 per cent of the total car fleet.

A car fleet is, in other words, an inert matter. This becomes even more visible when we plot average CO_2 emission rates, as in Figure 11. The red curve, representing the *car fleet's* mean type approval rate of CO_2 emissions, lags 10-15 years behind the green curve, which represents the *newest generation* of cars. Moreover, the *real-world* CO_2 emissions, shown in blue, are considerable higher than the *type approval* rates. This gap is widening, since the discrepancy between laboratory and on-the-road emission has been growing with later generations of cars (Mock et al. 2013, 2014).

To many planners and politicians, the fiscal consequences of a policy to combat GHG emissions are of great concern. Even these aspects can be illuminated in a BIG model run. In Figure 12, we show the fiscal impact of a policy introducing a steadily steeper purchase tax for high emission cars, while the low emission cars, such as PHEVs, are taxed less heavily than today. The policy will generate increasing purchase tax revenue, since many people will continue to buy ICE vehicles, but reduced revenue from fuel tax, as more and more vehicles are electrified. The increase in electricity tax revenue is quite small, by comparison.

[9] In 2010, the average retail price of ICE cars was 142 per cent higher than the import value. This difference covers not only purchase tax and VAT, but also the wholesale and retail dealers' margin.

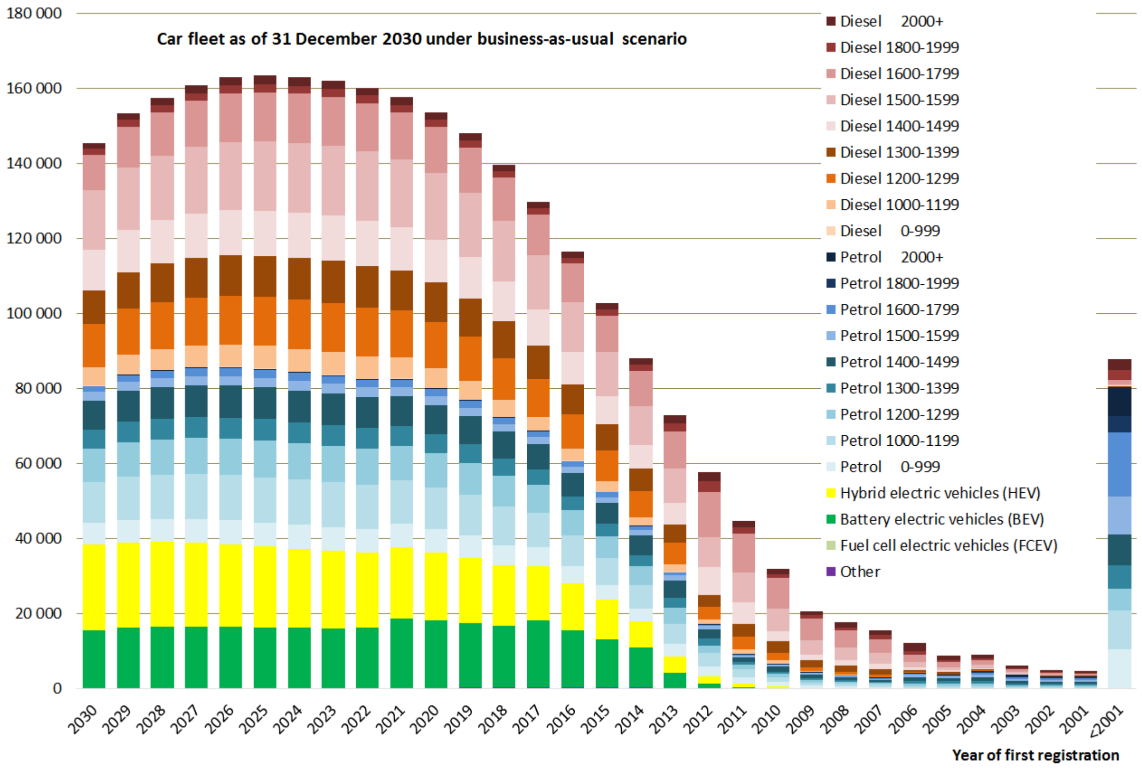


Figure 9. Business-as-usual scenario. Projected Norwegian passenger car fleet at year-end 2030, by fuel type, kg curb weight and year of first registration.

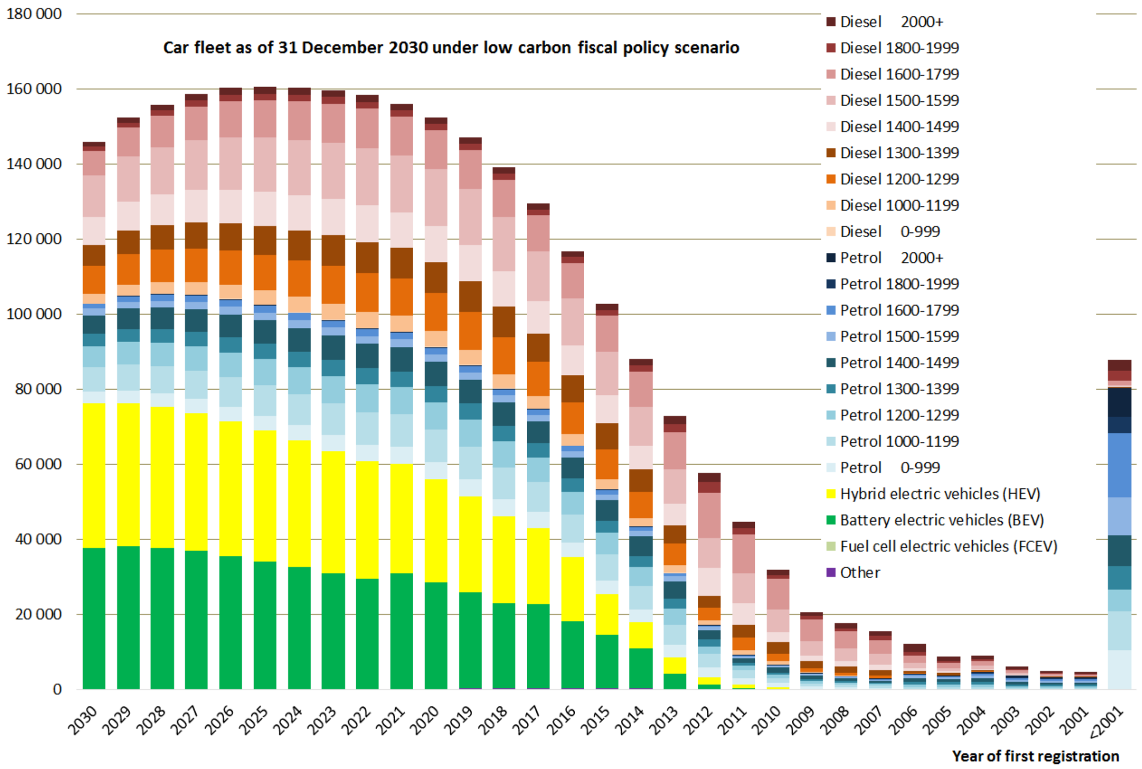


Figure 10. Low carbon fiscal policy scenario. Projected Norwegian passenger car fleet at year-end 2030, by fuel type, kg curb weight and year of first registration.

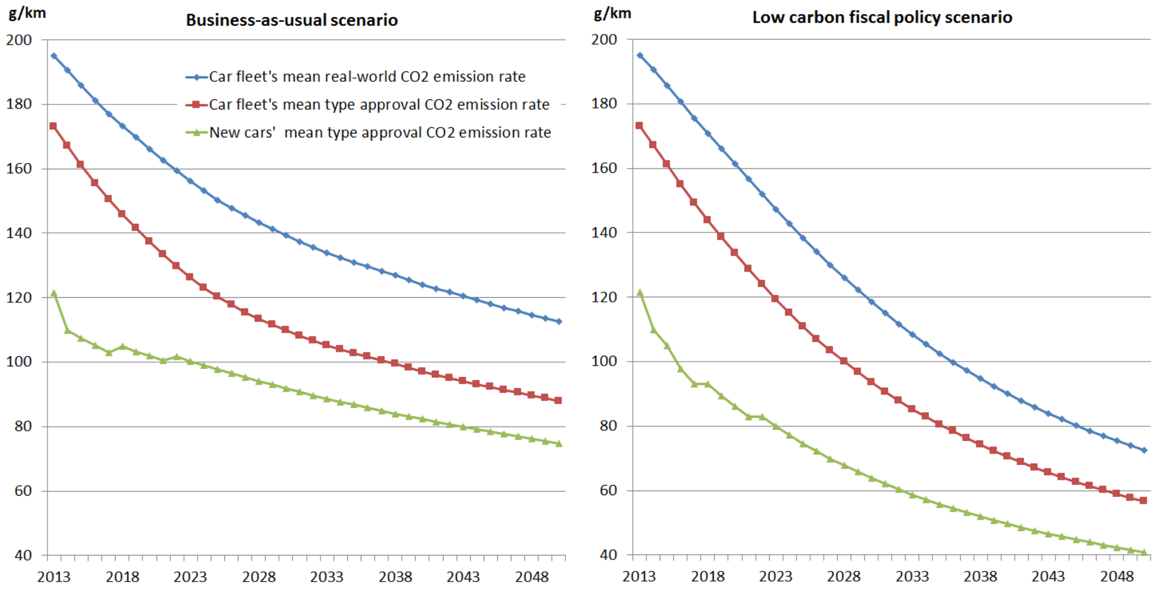


Figure 11. Passenger cars' average CO_2 emission rates under business-as-usual and low carbon fiscal policy scenarios 2013-2050. Source: Fridstrøm et al. (2014).

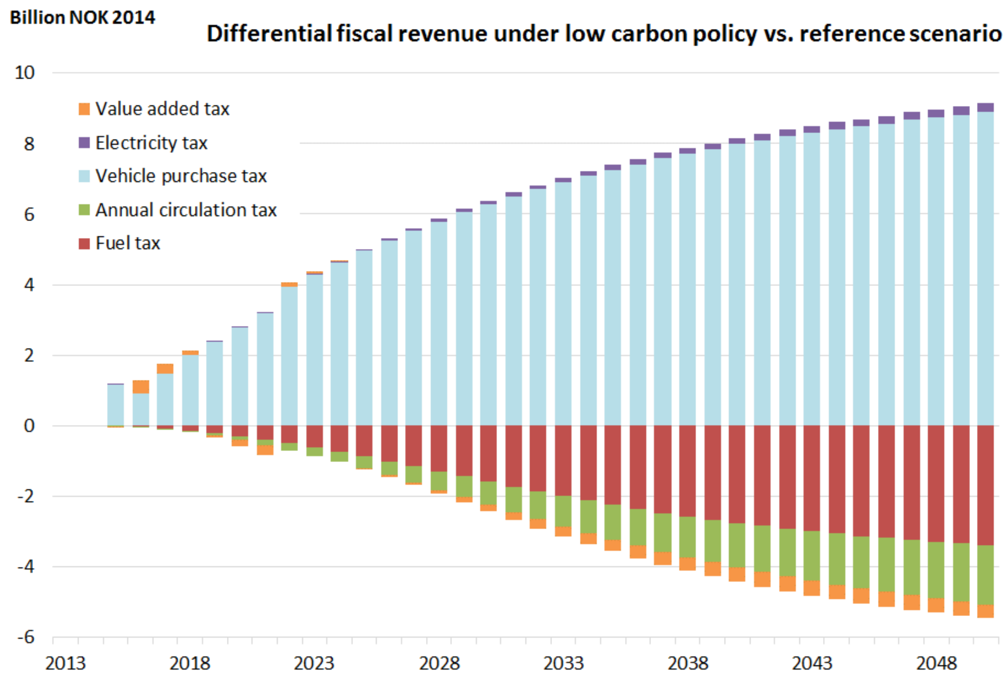


Figure 12. Differential fiscal revenue between low carbon policy and business-as-usual scenarios. Source: Fridstrøm and Østli (2015).

5 Discussion

The BIG stock-flow cohort model constitutes a bottom-up approach to vehicle fleet forecasting. New car registrations follow from a disaggregate discrete choice model based on sales data for individual passenger car models. The flows and stocks characterising the car fleet are specified at a somewhat coarser, yet relatively detailed level, describing each year's stocks and flows of vehicles as the aggregation of 22 x 31 = 682 mutually exclusive and exhaustive cells. This accurate bottom level accounting guards against gross errors of aggregation, without, of course, preventing the model user from producing and presenting results at a much less detailed level.

In the interest of tractability, it has been necessary to make certain simplifying assumptions. As a default option, age and segment specific scrapping, deregistration and second hand car import rates have been assumed constant, calibrated in accordance with the empirical means observed over a two-year period. Also, for lack of better information, certain parameters have been assumed invariant across vehicle segments or cohorts.

Also, since annual mileage factors are set exogenously for each cell in the 22 x 31 vehicle stock matrix, and – as a default – do not vary over time, the model does not take account of rebound effects, such as when aggregate road travel demand increases in response to a lower average per km energy cost. Moreover, since there is no behavioural relation explaining aggregate car ownership or acquisition, there is also a possible rebound effect – not accounted for – in terms of a larger (or smaller) car fleet. As demonstrated by D'Haultfoeuille et al. (2013) in the context of the French feebate system for car purchases, such effects could be quite important.

With the present version of the BIG algorithm, rebound effects must be calculated outside the model, by combining BIG model runs with travel demand modelling. We have, in a companion paper (Fridstrøm et al. 2015), used the national and regional travel demand systems for Norway to assess the effect of a 50 per cent lower average per km fuel cost, brought about by fiscal incentives bearing on new car purchases. Car travel demand is then projected to increase by 15 per cent, as measured in vehicle kilometres on short-haul (urban) trips, and by 48 per cent on long-haul (interurban) trips. As measured in terms of overall CO_2 emissions, however, the rebound effect is more important in the urban than in the interurban setting. This is so because, while short urban car trips compete with generally more climate friendly public transport, long-haul interurban car trips in Norway compete primarily with the air mode (Fridstrøm et al. 2014).

Our stock-flow cohort model differs from virtually all other car fleet models reported in the literature in that it contains no information on the vehicle owners or their households. Hence the model cannot predict the effect of changes occurring to the car *owners*, such as increased income, rather than to the vehicles themselves. The benefit of this approach, however, is one of considerable simplification, leaving room for a more detailed, more complete and less aggregate description of the vehicle stock. Also, it means that no input is required on such variables as household structure, population and income growth, or transport infrastructure and prices, in order for the model to produce a forecast.

The BIG stock-flow model is primarily a coherent accounting framework, into which economic, behavioural or technological relations can be built. Apart from the discrete choice model of new car purchases, the framework itself is almost void of behavioural content. But the accounting identities allow for several useful deductions, such as when we estimate the time lag between changes occurring to, respectively, the flow of new cars registered and the stock of cars, or when the survival rates of different vehicle segments are derived from a few years' data on the stock of cars and the flow of vehicles scrapped.

Potential extensions and improvements of the stock-flow model include (i) the integration, into the framework, of behavioural relations endogenising, e. g., scrapping rates, aggregate vehicle miles travelled, or aggregate car purchases, including second hand import, and (ii) the extension to a wider set of knock-on effects covered, so as to include, e. g., particulate matter, NO_X emissions, or accidents.

6 Conclusions

Stock-flow vehicle cohort models exploit the accounting relations inherent in the processes of fleet development, new car acquisition, scrapping, import, export and deregistration, in a way very similar to how, in a demographic forecasting model, the flows of births, deaths, immigrants and emigrants would influence and depend on the stock of individuals, i. e. the human population.

Stock-flow cohort modelling of the car fleet is a powerful and handy tool for policy analysis. Even quite simple and straightforward accounting relations may provide important insights into the dynamics of fleet development. A particularly useful piece of information concerns the amount of inertia involved, as characterised, e. g., by the time lag between technological improvements affecting new vehicles and their penetration into the car fleet.

It is possible to incorporate, into the stock-flow modelling framework, interesting and useful behavioural relations, explaining aggregate passenger car ownership and travel demand, scrapping and survival rates, or consumer choice in the market for new cars. Even without such behavioural relations, the framework is useful for analysing and predicting policy dependent developments in terms of energy use, GHG emissions, local pollution, accident rates, fiscal impact and economic costs.

Far from presupposing sophisticated computer programming, the recursive stock-flow cohort model can be implemented by means of standard spreadsheet software.

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